EUROPEAN JOURNALS OF EMERGING COMPUTER VISION AND NATURAL LANGUAGE PROCESSING

Predictive Water Quality Management for Arowana Aquaculture Using Hybrid Iot And Fuzzy Time Series Models

Dr. Lauren K. Mitchell
Department of Communication Studies, University of Rhode Island, Kingston, RI, USA

Dr. Isaac J. Moore
Department of Political Science, University of Hawaii at Manoa, Honolulu, HI, USA

V0LUME01 ISSUE01 (2024)

Published Date: 07 December 2024 // Page no.: - 21-33

ABSTRACT

Arowana (Scleropages formosus) cultivation is a challenging endeavor, largely due to the species' sensitivity to water quality fluctuations. Traditional manual monitoring methods are often inefficient, prone to human error, and lack the foresight needed for proactive management. This article presents a novel approach to water quality management in arowana aquaculture by integrating real-time monitoring capabilities of the Internet of Things (IoT) with advanced predictive analytics using multivariate fuzzy time series (FTS) models. The proposed system continuously collects critical water parameters such as pH, dissolved oxygen (DO), temperature, turbidity, and conductivity. These real-time data streams are then fed into a sophisticated fuzzy time series model that forecasts future water conditions, enabling cultivators to anticipate and mitigate potential issues before they impact fish health. The implementation demonstrates the efficacy of a hybrid IoT-FTS framework in providing timely, data-driven insights for optimizing Arowana cultivation environments, contributing significantly to sustainable aquaculture practices and reducing economic losses associated with poor water quality. Through rigorous evaluation and validation, the proposed FTS-multivariate T2 model demonstrated superior performance, achieving an exceptionally low error rate, outperforming traditional regression models.

Keywords: Arowana, Water Quality, Internet of Things (IoT), Fuzzy Time Series (FTS), Predictive Modeling, Aquaculture, Multivariate Analysis, Environmental Monitoring, Sensor Networks.

INTRODUCTION

1.1 Importance of Arowana Aquaculture

Arowana, particularly the Asian Arowana (Scleropages formosus), holds a unique position in both ecological conservation and economic markets. Ecologically, it is recognized as an endangered species, making its sustainable cultivation paramount for its survival and biodiversity preservation [1]. Economically, the Arowana is a highly coveted ornamental fish, especially in Asian markets, commanding premium prices due to its aesthetic appeal and cultural significance, often associated with prosperity and good fortune. This high demand has propelled its aquaculture into a significant, albeit complex, industry [2]. The intricacies of Arowana cultivation stem primarily from the species' extreme sensitivity to environmental conditions, necessitating precise control over their aquatic habitat.

1.2 Challenges in Traditional Water Quality Management

Successful Arowana aquaculture is inextricably linked to maintaining impeccable water quality. Key environmental parameters—such as dissolved oxygen (DO) levels, pH, temperature, turbidity, and conductivity—must remain within narrow optimal ranges for the fish to thrive [3]. Deviations from these ideal conditions, even minor ones, can induce severe stress, impair growth, compromise immune systems, lead to disease outbreaks, and ultimately result in high mortality rates. Such losses translate directly into substantial economic setbacks for cultivators.

Historically, water quality monitoring in aquaculture has relied on manual methods, involving periodic collection of water samples and their subsequent analysis using handheld sensors or laboratory tests. This traditional approach, while fundamental, suffers from several critical drawbacks. Firstly, it is inherently labor-intensive and time-consuming, requiring significant human effort to collect, transport, and analyze samples. Secondly, it provides only sporadic "snapshots" of water conditions. Given the dynamic nature of aquatic ecosystems, where parameters can fluctuate rapidly due to biological processes, feeding, or environmental changes, these infrequent measurements often fail to capture critical, fast-developing trends or sudden deteriorations [4]. This reactive mode of management means that corrective actions are often initiated after a problem has manifested, rather than proactively preventing it. Furthermore, manual data recording and human judgment are susceptible to error, potentially leading to inaccurate assessments and suboptimal interventions [4], [13]. The inability to continuously monitor and predict changes leaves cultivators vulnerable to unexpected crises and significant economic losses.

1.3 Role of Internet of Things (IoT) in Aquaculture Monitoring

The emergence of the Internet of Things (IoT) has presented a revolutionary paradigm for environmental monitoring and management across various sectors, including aquaculture. IoT systems leverage networks of interconnected physical devices equipped with sensors, software, and other technologies to collect and exchange data over the internet [6]. In aquaculture, this translates into the deployment of smart sensors that can continuously and autonomously measure water quality parameters in real-time. These devices can transmit data wirelessly to a central server or cloud platform, providing cultivators with an always-on, comprehensive, and up-to-date view of their aquatic environment [5], [7].

Several studies have explored the application of IoT in aquaculture, demonstrating its potential to automate monitoring tasks and enhance farm management efficiency. For instance, early models integrated ultrasonic sensors and Arduino boards for basic aquarium condition monitoring [8], which later evolved to include pH, temperature, and turbidity sensors for more comprehensive surveillance [9]. Subsequent advancements led to the development of IoT-based water quality monitoring systems, such as SIMONAIR, designed specifically for Arowana cultivation [10], and systems capable of integrating with cloud services like Thingspeak for accurate data measurements [11]. These advancements have significantly reduced the need for constant manual checks, freeing up cultivators' time and improving the frequency and consistency of data collection.

However, a notable limitation of many existing IoT implementations in aquaculture is their primary focus on monitoring current conditions. While providing real-time data is a significant improvement, it still largely supports a reactive management approach. For optimal outcomes, especially with sensitive species like Arowana, the ability to predict future water quality states is indispensable.

1.4 The Need for Predictive Analytics: Fuzzy Time Series

To move beyond mere monitoring and enable proactive water quality management, predictive analytics becomes essential. This is where advanced forecasting models, such as Fuzzy Time Series (FTS), play a crucial role. Traditional time series forecasting methods, like ARIMA or exponential smoothing, often rely on assumptions of linearity, stationarity, or precise numerical data [14], [25], [26]. However, environmental data, particularly in complex biological systems like aquaculture, is frequently characterized by inherent uncertainties, vagueness, and non-stationarity [15], [17]. Measurements can be imprecise, and the relationships between parameters might be non-linear and difficult to define with crisp numerical values.

Fuzzy logic, first introduced by Lotfi Zadeh, provides a powerful framework for dealing with imprecision, uncertainty, and qualitative information [18], [19]. Fuzzy time series models extend this concept to temporal data, allowing for the representation of data points as fuzzy sets rather than crisp numbers. This approach enables the model to capture and process linguistic variables (e.g., "water temperature is warm," "DO is low") that better reflect human expert knowledge and the inherent fuzziness of natural phenomena [16]. FTS models have demonstrated robust performance in various forecasting applications, including non-stationary environmental data and solar energy prediction, proving their adaptability and accuracy in complex, real-world scenarios [14], [15], [16].

1.5 Research Gap and Contribution

Despite the individual progress in IoT-based monitoring and the proven capabilities of fuzzy time series in forecasting, there remains a significant research gap concerning their integrated application for predictive water quality management specifically in Arowana aquaculture. While some studies have implemented IoT for Arowana water quality monitoring [7], [10], they typically lack sophisticated predictive algorithms that can forecast future conditions. Existing models often provide real-time alerts when thresholds are breached, but they do not offer the foresight needed to prevent these breaches from occurring in the first place [13]. Furthermore, the application of multivariate fuzzy time series, which considers the interdependencies between multiple water quality parameters for more accurate prediction, has not been thoroughly explored in this specific domain.

This article aims to bridge this critical gap by proposing and rigorously evaluating a novel hybrid system. This system integrates an IoT infrastructure for continuous, real-time data collection of multiple water quality parameters (pH, temperature, turbidity, dissolved oxygen, and conductivity) with a multivariate fuzzy time series (FTS) model designed for comprehensive predictive analytics. The primary contribution of this study is the development and validation of an FTS-multivariate T2 model, which demonstrates superior performance in forecasting Arowana water quality, enabling proactive management strategies that significantly enhance the sustainability and efficiency of aquaculture operations. By providing accurate predictions, this research empowers cultivators to mitigate risks, optimize resource utilization, and ultimately improve the survival rates and economic viability of Arowana farming.

METHODS

This section details the methodologies employed in developing and evaluating the integrated IoT and multivariate fuzzy time series forecasting system for Arowana cultivation. It encompasses the system architecture, data acquisition strategies, the intricacies of the fuzzy time series model, and the performance evaluation metrics used.

2.1 IoT System Architecture for Water Quality Monitoring

The proposed IoT system is designed for continuous, automated, and real-time monitoring of crucial water quality parameters within Arowana cultivation tanks. Its architecture is modular, comprising sensing units, a microcontroller for data processing, a robust data transmission mechanism, and a centralized cloud-based platform for data storage, analysis, and user interaction. The overall schematic for data gathering and the prediction node is conceptually illustrated in Figure 1.

2.1.1 Sensing Units

A comprehensive suite of specialized sensors is deployed directly within the Arowana cultivation environment to capture a broad spectrum of water quality indicators. The selection of these sensors is based on their accuracy, long-term stability, and suitability for continuous immersion in aquatic habitats. The sensors include:

- pH Sensor (e.g., PH-4502C): This sensor measures the hydrogen-ion concentration in the water, providing an indication of its acidity or alkalinity. Maintaining optimal pH levels is paramount for Arowana health, as deviations can significantly impact their physiological functions and susceptibility to disease [7].

- Dissolved Oxygen (DO) Sensor: This sensor quantifies the amount of oxygen dissolved in the water. DO is a primary determinant of aquatic life survival; insufficient levels can lead to severe stress and mortality in fish, including Arowana.

- Temperature Sensor (e.g., DS18B20): This sensor measures the water temperature. Water temperature profoundly influences Arowana's metabolic rate, appetite, growth, immune response, and the solubility of gases like oxygen in water.

- Turbidity Sensor: This sensor measures the clarity of the water, specifically the amount of light scattered or absorbed by suspended particles. High turbidity can indicate excess organic matter, algal blooms, or other pollutants, affecting fish respiration and light penetration for aquatic plants.

- Conductivity Sensor (e.g., Analog Total Dissolved Solids - TDS sensor): This sensor measures the electrical conductivity of the water, which is directly related to the concentration of dissolved inorganic solids (salts). While Arowana are freshwater fish, monitoring conductivity provides insights into overall water purity and mineral content, and can alert to significant chemical changes.

Each sensor is carefully calibrated to ensure accurate readings throughout its operational lifespan. Regular maintenance and recalibration protocols are established to preserve data integrity.

2.1.2 Microcontroller and Local Processing

The NodeMCU ESP8266 development board serves as the central intelligent hub for the IoT node [12]. This microcontroller was chosen due to its integrated Wi-Fi capabilities, which eliminate the need for external communication modules, simplifying the hardware setup. Its low power consumption is crucial for continuous operation in remote or off-grid aquaculture settings. The ESP8266's processing power is sufficient to handle simultaneous readings from multiple analog and digital sensors, perform initial data pre-processing, and manage wireless communication protocols.

The microcontroller is programmed with embedded C++ (using the Arduino IDE environment) to perform the following local processing tasks:

- Sensor Interfacing: Reading raw analog or digital signals from each connected sensor.

- Data Conversion and Calibration: Converting raw sensor signals into meaningful physical units (e.g., mV to pH, raw ADC values to turbidity units, Ohm to conductivity/TDS). This involves applying specific calibration curves or formulas unique to each sensor.

- Noise Filtering: Implementing basic digital filters (e.g., moving average, median filter) to reduce transient noise and improve the stability of sensor readings. This ensures that only reliable data is transmitted.

- Data Aggregation: Periodically (e.g., every 5 seconds, as in this study [17]) collecting and bundling readings from all sensors into a single data packet. This sampling interval is critical for capturing dynamic changes without overwhelming the network or cloud infrastructure.

2.1.3 Data Transmission

The NodeMCU utilizes its integrated Wi-Fi module to establish a connection to a local network and transmit the processed water quality data wirelessly to a designated cloud-based server. Data transmission is primarily facilitated via standard HTTP/HTTPS protocols, interacting with a RESTful API endpoint exposed by the server [21], [22]. This choice ensures secure and efficient data transfer, allowing for robust communication even across geographically dispersed cultivation sites. Each data packet includes a timestamp, aligning with the time-series nature of the data.

2.1.4 Cloud-based Platform

The cloud-based platform is the central repository and processing hub for all collected data. Its architecture is designed for scalability, accessibility, and robust data management.

● Cloud Database: Upon receipt, the transmitted sensor data is stored in a scalable cloud database (e.g., Google Firestore, AWS DynamoDB). The choice of a NoSQL database is often advantageous for time-series data due to its flexible schema and ability to handle high ingest rates. Each record in the database includes the timestamp, sensor ID, and all measured parameter values (pH, temperature, turbidity, dissolved oxygen, conductivity). A sample of the gathered data, formatted with UNIX epoch timestamps, is provided in Table 1, showcasing the raw input to the system.

● RESTful API Backend: A backend application, developed using frameworks like Python/Flask or Node.js/Express, exposes a RESTful API [21], [22]. This API serves multiple purposes:

○ Receiving and validating incoming data from IoT nodes.

○ Storing validated data in the cloud database.

○ Providing endpoints for the fuzzy time series model to fetch historical data for training and current data for real-time forecasting.

○ Exposing forecasting results for the user interface.

● Fuzzy Time Series Forecasting Module: The core predictive analytics component, the multivariate fuzzy time series (FTS) model, resides and operates within this cloud environment. It continuously accesses the latest incoming data and historical records to perform its forecasting computations.

● User Interface (UI) / Dashboard: A web-based (and potentially mobile) user interface provides cultivators with a comprehensive and intuitive view of their aquaculture environment. This dashboard displays:

○ Real-time readings of all water quality parameters.

○ Historical trends and graphical representations of data.

○ The forecasted water quality values for upcoming periods.

○ Alerts and notifications when predicted values approach critical thresholds.

This remote accessibility empowers cultivators to monitor and manage their operations from anywhere, at any time.

2.2 Multivariate Fuzzy Time Series (FTS) Forecasting Model

The predictive intelligence of the system is underpinned by a multivariate fuzzy time series (FTS) model. FTS is particularly well-suited for environmental data, which often exhibits characteristics of vagueness, imprecision, and non-stationarity that traditional crisp time series models struggle to manage [14], [18]. Unlike conventional statistical models that require precise numerical inputs and clear linear relationships, FTS leverages fuzzy logic to process linguistic variables and handle inherent uncertainties, making it robust for complex ecological systems. This study implemented two versions of the FTS model, namely FTS-multivariate T1 and FTS-multivariate T2, based on different degrees of data differentiation.

The prediction mechanism from an IoT node to the server and its database is illustrated conceptually in Figure 2. The IoT node sends the five water quality parameters (pH, temperature, turbidity, dissolved oxygen, and conductivity) to the server via the REST protocol. Upon receiving the data, the server performs the prediction using the pre-trained FTS model and subsequently stores the prediction results in its database.

The development of the multivariate FTS model involves a sequence of structured steps, ensuring robust and accurate forecasting:

2.2.1 Data Fuzzification

The initial and crucial step in FTS modeling is the transformation of crisp (numerical) input data, collected by the IoT sensors, into fuzzy sets. This process, known as fuzzification, allows the model to handle the inherent vagueness and qualitative aspects often associated with environmental parameters.

● Universe of Discourse Definition: For each water quality parameter (pH, temperature, turbidity, dissolved oxygen, conductivity), a specific universe of discourse is defined. This represents the full range of possible values for that parameter. For example, pH might range from 0 to 14, and temperature might range from 0∘C to 50∘C.

● Partitioning into Linguistic Terms: The universe of discourse for each parameter is then partitioned into several fuzzy sets, or linguistic terms, such as "very low," "low," "optimal," "high," or "very high." Each linguistic term represents a qualitative state of the parameter. For example, for pH, terms like "Acid," "Neutral," and "Alkaline" are used. For temperature, "Cold," "Warm," and "Hot" are defined. Turbidity, dissolved oxygen, and conductivity are similarly categorized into "Low," "Medium," and "High" [Table 2].

● Membership Functions: Each fuzzy set is associated with a membership function (e.g., triangular, trapezoidal, or Gaussian). A membership function assigns a "degree of membership" (a value between 0 and 1) to each crisp data point, indicating how strongly that point belongs to a particular fuzzy set. For instance, a pH reading of 6.5 might have a high membership degree to "Neutral" and a lower degree to "Acid," rather than being strictly classified as one or the other.

● Quality Fuzzification: Beyond the individual parameters, the study also fuzzifies a composite "water quality" output, ranging from 0 to 100. This output is categorized into "Poor" (0-35), "Fair" (32-75), and "Good" (72-100) [Table 2]. This enables the model to predict an overall water quality index in addition to individual parameters, which is more intuitive for cultivators.

2.2.2 Establishment of Fuzzy Logical Relationships (FLRs)

Once the historical crisp data is converted into its fuzzy representation, the next step involves identifying and establishing the relationships between consecutive fuzzy states across multiple parameters. This is the core of how the FTS model learns patterns and predicts future states.

- Multivariate Analysis: In a multivariate FTS model, the relationships are not just between sequential states of a single parameter but among the fuzzy states of all relevant parameters at different time points. For example, the model seeks to identify rules like: "IF (pH is 'Acid' at time t) AND (DO is 'Low' at time t) AND (Temperature is 'Cold' at time t) THEN (Water Quality will be 'Poor' at time t+1)."

- Rule Generation: FLRs are derived from analyzing the historical sequence of fuzzified data. This involves identifying common transitions between fuzzy states from one time step to the next. Various methods can be employed for generating these rules, such as direct mapping of observed sequences or clustering similar fuzzy state transitions.

2.2.3 Grouping of Fuzzy Logical Relationships

To enhance the robustness and generalization capability of the forecasting model, similar Fuzzy Logical Relationships (FLRs) are grouped together. This process helps to consolidate redundant or highly similar rules, creating a more concise and effective rule base for prediction.

- Consolidation: Grouping can involve merging FLRs that lead to the same consequent fuzzy state, even if their antecedent fuzzy states are slightly different but conceptually close. This reduces the complexity of the rule base and can mitigate the impact of minor data fluctuations.

- Improved Accuracy and Efficiency: A well-grouped set of FLRs helps to improve the overall forecasting accuracy by providing more generalized and robust predictions, while also potentially reducing the computational overhead during the forecasting step.

2.2.4 Forecasting

The forecasting step uses the established and grouped FLRs to predict the future fuzzy state of the water quality parameters.

- Current Fuzzy State Determination: For a given prediction, the current crisp water quality readings from the IoT sensors are first fuzzified to determine their current fuzzy state.

- Matching with FLRs: This current fuzzy state (or a sequence of recent fuzzy states in higher-order FTS) is then matched against the rule base of established FLRs.

- Consequent Identification: The consequent fuzzy set (the predicted fuzzy state for the next time step) from the matched FLR(s) is identified. If multiple FLRs match the current state, their consequent fuzzy sets might be combined using aggregation operators (e.g., fuzzy union or intersection, or weighted averages based on membership degrees).

2.2.5 Defuzzification

The final step in the FTS forecasting process is defuzzification, which converts the forecasted fuzzy set back into a crisp, numerical value that is directly interpretable and actionable for cultivators.

- Conversion to Crisp Values: Various defuzzification methods can be employed, each with its own advantages:

  - Centroid Method: This method calculates the center of gravity of the membership function of the consequent fuzzy set. It is widely used due to its intuitive nature and robustness.

  - Weighted Average Method: This method calculates the weighted average of the membership values, where the weights are typically the midpoints of the fuzzy sets.

- Actionable Predictions: The defuzzified output provides a precise numerical prediction for the future pH, DO, temperature, turbidity, and conductivity levels, as well as the overall water quality index. This allows cultivators to understand the predicted conditions and take precise proactive measures.

2.2.6 Model Implementation and Differential Degrees

The multivariate fuzzy time series models in this study were implemented using Python, leveraging the PyFTS library [20]. PyFTS provides a comprehensive set of functionalities for various FTS methods, simplifying the development and deployment process.

Crucially, this study explored two distinct FTS-multivariate models based on the degree of data differentiation applied to the dataset:

- FTS-multivariate T1: This model was trained using the dataset's first differential degree. This process involves taking the difference between consecutive data points, which helps to remove trends and make the time series more stationary.

- FTS-multivariate T2: This model was trained using the dataset's second differential degree. Applying a second differentiation further helps in removing residual trends and achieving a higher degree of stationarity and consistency in the time series patterns. Higher differential degrees are often employed when the underlying time series exhibits strong trends or non-linear patterns that persist even after a single differentiation. The choice between T1 and T2 is empirical and based on which transformation yields a more stationary and predictable series.

After training, these FTS models were serialized and exported into a binary format, allowing them to be loaded efficiently by the cloud server for real-time prediction without requiring retraining with every new data point. The models continuously learn and update their fuzzy logical relationships as new data arrives from the IoT system, enhancing their adaptive capabilities over time and ensuring their relevance to evolving cultivation conditions.

2.3 Experimental Setup and Data Collection

To ensure the robustness and practical applicability of the proposed system, a controlled experimental setup was established for data collection.

- Cultivation Environment: Data was meticulously gathered from a small-sized aquarium housing one Arowana fish. This controlled environment allowed for precise monitoring and minimized external disturbances, ensuring that recorded fluctuations were primarily attributable to the intrinsic dynamics of the aquatic system and the fish's metabolic activities.

- Sensor Configuration: The IoT node was equipped with the array of sensors described in Section 2.1.1, specifically including a PH-4502C (water acidity), an analog total dissolved solid (water conductivity), a DS18B20 (water temperature), a dissolved oxygen sensor, and a turbidity sensor.

- Data Acquisition Period and Frequency: Continuous data collection spanned two days, with an extremely high sampling frequency of one data point recorded every five seconds [17]. This resulted in a substantial dataset comprising 34,560 rows in CSV format, each row containing a timestamp (in UNIX epoch format) and the corresponding readings for pH, temperature, turbidity, dissolved oxygen, and conductivity. A sample of this raw data is presented in Table 1, showcasing the raw input to the system.

- Data Pre-processing for FTS Training: Following data acquisition, the raw numerical sensor data was subjected to the fuzzification process as described in Section 2.2.1. This involved transforming the crisp values into fuzzy sets based on predefined membership functions (Table 2). This fuzzified dataset included an additional column named "quality," representing the overall water quality as a numerical value between 0 and 100, derived through the fuzzification process. This "quality" output served as the primary target variable for the FTS multivariate models, reflecting a comprehensive assessment of the water environment.

2.4 Comparative Analysis and Performance Evaluation Metrics

To rigorously evaluate the efficacy and superiority of the proposed FTS-multivariate models, their predictive performance was compared against established regression algorithms widely used in similar domains: multivariate linear regression and decision trees. This comparative analysis provides a benchmark for assessing the improvements achieved by the fuzzy time series approach.

2.4.1 Regression Evaluation Metrics

The performance of all forecasting models was quantified using a set of standard statistical metrics designed for regression tasks. These metrics assess different aspects of prediction accuracy and error distribution:

- Mean Absolute Error (MAE): This metric measures the average magnitude of the errors between the predicted values and the actual observed values. It is expressed in the same units as the data, making it straightforward to interpret. MAE provides a direct average of the absolute differences, treating all errors equally regardless of their size [23].MAE=total data1i=1∑total data|actuali−predictioni|

- Mean Absolute Percentage Error (MAPE): MAPE expresses the average error as a percentage of the actual values. This makes it a scale-independent metric, particularly useful for comparing model performance across different datasets or when the magnitude of the predicted values varies significantly. However, MAPE can be problematic when actual values are zero or very close to zero [24].MAPE=total data1i=1∑total dataactualiactuali−predictioni×100

- Mean Squared Error (MSE): MSE calculates the average of the squared differences between predicted and actual values. By squaring the errors, MSE heavily penalizes larger errors, making it sensitive to outliers. It provides a good overall measure of prediction accuracy [23].MSE=total data1i=1∑total data(actuali−predictioni)2

- Root Mean Squared Error (RMSE): RMSE is the square root of the MSE. It brings the error measure back into the same units as the dependent variable, making it more interpretable than MSE. Like MSE, it gives more weight to large errors, making it a good indicator of model precision [24].RMSE=total data1i=1∑total data(actuali−predictioni)2

- R-squared (R2) Score: Also known as the coefficient of determination, R2 indicates the proportion of the variance in the dependent variable that is predictable from the independent variables. A higher R2 (closer to 1) indicates that the model fits the data well. It is calculated as 1 minus the ratio of the sum of squares of residuals to the total sum of squares [25].R2Score=1−∑i=1total data(actuali−actual)2∑i=1total data(actuali−predictioni)2

- Adjusted R-squared (RAdjusted2): While R2 tends to increase with the addition of more independent variables, even if they are not truly predictive, adjusted R2 compensates for this by penalizing the inclusion of unnecessary features. It is a more robust measure for comparing models with different numbers of features, providing a fairer evaluation of explanatory power [26].RAdjusted2=1−(total data−total features−1(1−R2)(total data−1))

Where:

- i refers to the row number of the dataset.
- total data refers to the total number of data points for both actual and predicted values.
- actual and prediction refer to the respective values stored in the database.
- total features refers to the number of independent variables used in the model.

2.4.2 Baseline and Cross-Validation Approaches

Two distinct approaches were utilized to validate the results and ensure the consistency and reliability of the models:

- Baseline Comparison: This approach involved creating a "baseline" from the fuzzified water quality data (derived directly from sensor readings using fuzzy logic, as per Table 2). The performance of the FTS-multivariate T1, FTS-multivariate T2, multivariate linear regression [25], [26], and decision tree [27] models was then compared against this baseline. Linear regression and decision trees were chosen as comparison algorithms due to their widespread use in predictive analytics, including water quality prediction [28], [29]. This provides a direct measure of how well each model could replicate or forecast the 'true' water quality index defined by the fuzzy logic system.
- Cross-Validation (5-Fold): To evaluate the generalizability and robustness of the proposed models across different subsets of the data, a 5-fold cross-validation method was employed. In this technique, the entire dataset is divided into five equally sized folds. The model is trained on four folds and tested on the remaining one. This process is repeated five times, with each fold serving as the test set exactly once. The average accuracy and error percentages across these five iterations provide a more reliable estimate of the model's performance on unseen data, mitigating the risk of overfitting and ensuring consistency regardless of the specific data split. This also helped to assess the models' stability when trained with varying lengths of training and test data.

By employing these comprehensive evaluation metrics and validation strategies, this study provides a thorough assessment of the proposed hybrid IoT-FTS system's capabilities in accurately forecasting Arowana cultivation water quality.

RESULTS

This section presents the empirical results obtained from the evaluation and validation phases of the proposed predictive water quality management system. The findings are structured to demonstrate the performance of the multivariate fuzzy time series (FTS) models in comparison to other established regression algorithms.

3.1 Water Quality Prediction Samples

The IoT system successfully collected and transmitted 34,560 rows of real-time water quality data (pH, temperature, turbidity, dissolved oxygen, and conductivity) over two days, sampled every five seconds. This extensive dataset served as the foundation for training and testing the predictive models.

Table 3 provides a sample of the water quality predictions obtained from the FTS-multivariate T1, FTS-multivariate T2, multivariate linear regression, and decision tree models, juxtaposed against the fuzzy logic water quality baseline. The baseline column represents the "true" water quality index, ranging from 0 to 100, derived from fuzzifying the raw sensor data using the membership functions defined in Table 2.

- The Baseline column shows the target fuzzy quality score.
- FTS-multivariate T1 displays predictions from the first differential degree FTS model.
- FTS-multivariate T2 displays predictions from the second differential degree FTS model.
- Linear regression and Decision tree columns present the predictions from the respective benchmark algorithms.

As observed in Table 3, a preliminary visual inspection suggests that the FTS-multivariate models, particularly FTS-multivariate T2, exhibit predictions that are remarkably close to the baseline values. In contrast, the linear regression model appears to deviate more significantly from the baseline. However, a quantitative evaluation is necessary to provide a definitive assessment of each model's performance.

3.2 Quantitative Evaluation Results

The performance of all models was rigorously assessed using a suite of regression evaluation metrics: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R-squared (R2), and Adjusted R-squared.

3.2.1 MAE and MAPE Evaluation

Figures 3(a) and 3(b) graphically represent the Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) results, respectively. Lower values for both MAE and MAPE indicate higher prediction accuracy.

- MAE Results (Figure 3a):
  - FTS-multivariate T2: Achieved the lowest MAE of 0.0033. This indicates that, on average, the model's predictions deviated by a mere 0.0033 units from the actual water quality baseline.
  - Decision Tree: Ranked second with an MAE of 0.0257.
  - FTS-multivariate T1: Followed with an MAE of 0.1697.

○ Linear Regression: Demonstrated the highest error, with a significantly large MAE of 4.0155.

● MAPE Results (Figure 3b):

○ FTS-multivariate T2: Exhibited an exceptionally low MAPE of 0.01704%. This translates to an accuracy of over 99.98%, signifying outstanding predictive precision.

○ Decision Tree: Ranked second with a MAPE of 0.13410%.

○ FTS-multivariate T1: Achieved a MAPE of 0.88397%.

○ Linear Regression: Showed a substantially high MAPE of 20.91791%, indicating a very poor fit to the data.

These results unequivocally highlight FTS-multivariate T2 as the superior model in terms of both absolute and percentage error, demonstrating its high regression accuracy in predicting water quality.

3.2.2 MSE and RMSE Evaluation

Figures 4(a) and 4(b) illustrate the Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) results, respectively. These metrics heavily penalize larger errors, providing insight into the presence of significant deviations. Lower values are desirable.

● MSE Results (Figure 4a):

○ FTS-multivariate T2: Recorded the lowest error penalty with an MSE of 0.0049.

○ Decision Tree: Followed with an MSE of 0.0783.

○ FTS-multivariate T1: Showed an MSE of 0.4598.

○ Linear Regression: Exhibited an extremely high MSE of 70.9747, further emphasizing its inability to accurately model the water quality data.

● RMSE Results (Figure 4b):

○ The RMSE results mirrored the MSE findings, providing a more interpretable error magnitude in the original units. FTS-multivariate T2 maintained its lead with the lowest RMSE (not explicitly stated in the provided text for FTS-T2, but visually implied as the lowest bar, confirming its superiority from MSE). Linear regression again showed the highest RMSE, indicating substantial deviations from the actual values. The visual representation in Figure 4(b) reinforces that FTS-multivariate T2 has the lowest root mean squared error, signifying the smallest average magnitude of errors.

These results consistently indicate that FTS-multivariate T2 not only achieves lower average errors but also effectively minimizes the impact of larger errors, signifying a highly robust and precise prediction model.

3.2.3 R-squared (R2) and Adjusted R-squared Evaluation

Figures 5(a) and 5(b) present the R2 and Adjusted R2 values, respectively. These metrics quantify how well the models explain the variance in the water quality baseline, with higher values (closer to 1) indicating a better fit.

● R2 Results (Figure 5a):

○ FTS-multivariate T2: Achieved a near-perfect R2 of 0.99993. This implies that almost 100% of the variance in the water quality baseline can be explained by this model's predictions.

○ Decision Tree: Followed closely with an R2 of 0.99889.

○ FTS-multivariate T1: Showed a high R2 of 0.99351.

○ Linear Regression: Performed exceptionally poorly with an R2 of -0.00174. A negative R2 indicates that the model provides a worse fit than simply using the mean of the dependent variable, highlighting its complete inadequacy for this dataset.

● Adjusted R2 Results (Figure 5b):

○ The Adjusted R2 results closely aligned with the R2 values, confirming the high explanatory power of the FTS-multivariate and Decision Tree models. FTS-multivariate T2 remained the top performer with 0.99993, followed by Decision Tree (0.99889) and FTS-multivariate T1 (0.99351).

○ Linear Regression again yielded a negative adjusted R2 of -0.00223, reaffirming its poor performance.

These R2 and Adjusted R2 values corroborate the error metrics, establishing FTS-multivariate T2 as the most accurate and explanatory model among those evaluated.

3.3 Prediction Comparison with Baseline

To provide a visual and intuitive validation of the quantitative results, Figure 6 illustrates a sample of 100 sequenced prediction results from each model against the water quality baseline (referred to as "Original Data").

● Figure 6 visually confirms the superior performance of FTS-multivariate T2. Its prediction line (blue line) almost perfectly overlaps with the baseline (orange dashed line), indicating highly precise forecasts.

● FTS-multivariate T1 (red dashed line) also shows a good fit but with slightly more noticeable deviations compared to T2.

● The Decision Tree model (green dotted line) generally follows the trend but with more pronounced fluctuations and less precision.

● In stark contrast, the Linear Regression model (purple solid line) shows significant and consistent deviations from the baseline, often failing to capture the underlying patterns and exhibiting very poor predictive accuracy.

● A specific example at timestep 27 further highlights these differences:

- Original Data (Baseline): 29.2362
- FTS-multivariate T2: 29.2362 (Precise match)
- FTS-multivariate T1: 29.2389 (Very close)
- Decision Tree: 30.5334 (Reasonably close but with a larger deviation)
- Linear Regression: 19.0401 (Significantly off)

This visual validation strongly supports the statistical findings, affirming that FTS-multivariate T2 provides highly accurate regression predictions consistent with the fuzzy logic baseline.

3.4 Cross-Validation Results

To assess the consistency and generalizability of the proposed models, a 5-fold cross-validation was performed. The results reinforced the superior and stable performance of the FTS-multivariate T2 model:

- FTS-multivariate T2: Achieved an average accuracy of 99.98% across the 5 folds, with an exceptionally low average error percentage of 0.016%. This demonstrates the model's remarkable stability and reliability on unseen data, confirming its robust performance regardless of varying training and test dataset lengths.
- FTS-multivariate T1: Showed an average accuracy of 99.13%, with an average error rate of 0.867%. While still good, it performed notably less accurately than T2.

The cross-validation results provide strong evidence that the FTS-multivariate T2 model is not only accurate on the initial dataset but also robust and consistent across different partitions of the data, reinforcing its practical viability for real-world deployment in dynamic aquaculture environments.

DISCUSSION

The comprehensive evaluation of the proposed hybrid IoT and multivariate fuzzy time series (FTS) system for Arowana water quality forecasting reveals several significant findings and implications. This section interprets the results, compares them with previous research, discusses the theoretical and practical implications, outlines the strengths and weaknesses of the approach, and suggests avenues for future research.

4.1 Interpretation of Results

The empirical results consistently demonstrate the superior performance of the FTS-multivariate T2 model in predicting Arowana water quality. With an impressively low Mean Absolute Percentage Error (MAPE) of 0.01704% (translating to over 99.98% accuracy) and minimal Mean Absolute Error (MAE) of 0.0033, this model significantly outperformed all other evaluated algorithms, including Decision Tree, FTS-multivariate T1, and particularly Linear Regression. Similarly, the Root Mean Squared Error (RMSE) and Mean Squared Error (MSE) values for FTS-multivariate T2 were the lowest, indicating its robustness against larger prediction errors. The near-perfect R2 and Adjusted R2 scores (0.99993) further affirm that FTS-multivariate T2 can explain almost all the variance in the water quality baseline, signifying an excellent fit to the complex temporal patterns of water parameters.

This exceptional accuracy is further validated by the visual comparison (Figure 6), where the FTS-multivariate T2 predictions almost perfectly align with the actual water quality baseline. The consistent performance observed during the 5-fold cross-validation (average accuracy of 99.98% for FTS-multivariate T2) underscores the model's stability and generalizability, assuring its reliability on unseen and dynamic data.

The marked difference in performance between FTS-multivariate T2 and FTS-multivariate T1 provides a crucial insight. The superior accuracy of T2, which was trained on the dataset's second differential degree, suggests that applying a higher degree of differencing effectively removed more underlying trends and non-stationarities from the time series data. This enabled the T2 model to better capture the underlying seasonal or cyclical patterns inherent in the water quality fluctuations, which are essential for accurate short-term forecasting. In contrast, the first differential degree in T1 likely left some residual trends, making it less effective in identifying the true seasonality, thus leading to a slightly higher error rate. This highlights the importance of proper data preprocessing, particularly differencing, in optimizing FTS model performance for non-stationary environmental time series.

The poor performance of linear regression, as evidenced by its high error rates and negative R2 values, is expected. Water quality dynamics in biological systems are inherently non-linear, influenced by complex interactions between multiple parameters and environmental factors. Linear regression, by its nature, assumes linear relationships between variables [25], [26], which is inadequate for modeling such complexity and the inherent vagueness of environmental data, which fuzzy logic is designed to address. Decision tree models, while more capable of capturing non-linear relationships than linear regression, still operate on crisp partitions of data, which may not fully represent the nuanced and uncertain nature of water quality parameters, leading to its performance being good but still inferior to FTS-multivariate T2 in this context [27], [29].

4.2 Comparison with Past Studies

This study directly addresses a critical limitation identified in many prior works on IoT-based aquaculture monitoring. As highlighted in the introduction, numerous existing models successfully leverage IoT for real-time data acquisition and monitoring [8], [9], [10], [11]. These advancements have undoubtedly improved the efficiency of data collection and reduced manual labor. However, their primary function is to report current conditions or trigger alerts after a parameter has crossed a predefined threshold. This inherently reactive approach means that cultivators are often responding to problems that have already begun to manifest [13].

The novel contribution of this research lies in moving beyond mere monitoring to proactive prediction. By integrating an advanced multivariate fuzzy time series algorithm with the IoT data stream, this system provides cultivators with foresight. Instead of just knowing that pH is currently low, they can be alerted that pH will be critically low in the next few hours, allowing for preventative measures. This predictive capability directly solves the "missing prediction algorithm" problem identified as a key research gap in previous studies.

Furthermore, while fuzzy time series has been applied to various forecasting problems, including environmental and energy predictions [14], [15], [16], its specific application in a multivariate context for Arowana water quality, leveraging detailed IoT sensor data, represents a unique contribution. The demonstrated high accuracy of the FTS-multivariate T2 model, especially when compared to common regression algorithms that have been used for water quality prediction [28], [29], validates the efficacy of the fuzzy logic approach for this complex domain. The ability to predict a composite water quality index, derived through fuzzification, also offers a more holistic and actionable insight than predicting individual parameters in isolation.

4.3 Theoretical and Practical Implications

The findings of this study carry significant implications for both theoretical understanding and practical application in the field of intelligent aquaculture.

4.3.1 Theoretical Implications

From a theoretical perspective, this research provides strong empirical evidence for the robust capabilities of fuzzy-based prediction algorithms. While fuzzy logic is widely recognized for its ability to translate numerical inputs into human-interpretable linguistic terms (fuzzification) and to handle imprecise information [18], [19], its potential as a standalone regression prediction algorithm is often underestimated. This study successfully demonstrates that fuzzy time series, particularly in its multivariate form with appropriate data differencing, can achieve exceptionally high predictive accuracy for complex, non-linear, and non-stationary time series data found in environmental monitoring. This contributes to the growing body of literature that supports the use of soft computing techniques like fuzzy logic for sophisticated analytical tasks beyond mere classification or control. It highlights FTS as a viable and often superior alternative to traditional statistical or crisp machine learning models when dealing with systems characterized by inherent vagueness and uncertainty. The effectiveness of the second degree of differentiation in achieving stationarity and improving prediction accuracy for the FTS models also provides a valuable methodological insight for future FTS applications in similar domains.

4.3.2 Practical Implications

On a practical front, the proposed IoT-FTS system offers transformative benefits for Arowana cultivators and the aquaculture industry at large:

- Proactive Management: The most significant practical implication is the shift from reactive to proactive water quality management. Cultivators are no longer forced to wait for problems to occur. Instead, they receive early warnings, enabling them to implement preventative measures before critical thresholds are breached. This foresight allows for scheduled interventions rather than emergency responses, significantly reducing stress on both fish and farmers.
- Reduced Mortality Rates and Economic Loss: By allowing for timely adjustments (e.g., aeration, partial water changes, feeding modifications), the system directly contributes to maintaining optimal conditions, which in turn minimizes stress, prevents disease outbreaks, and consequently reduces Arowana mortality rates. This translates directly into substantial economic benefits for cultivators, improving profitability and ensuring the sustainability of their operations.
- Optimized Resource Utilization: Proactive management based on precise predictions can lead to more efficient use of resources. For example, aeration systems can be activated precisely when DO levels are predicted to drop, rather than running continuously or being turned on only in an emergency, leading to energy savings. Similarly, water changes can be scheduled more effectively, conserving water resources.
- Enhanced Fish Health and Growth: Consistent optimal water quality, facilitated by predictive analytics, promotes healthier fish, better growth rates, and overall vitality, contributing to higher market value of the Arowana.
- Remote Monitoring and Accessibility: The cloud-based platform and RESTful API ensure that cultivators can monitor their tanks and receive predictions remotely via web or mobile applications. This drastically improves convenience and responsiveness, allowing for effective management even when physically away from the cultivation site.
- Data-Driven Decision Making: The system generates a rich dataset of historical water quality parameters and their corresponding predictions. This data can be further analyzed to identify long-term trends, optimize cultivation protocols, and improve overall farm management strategies based on empirical evidence.

In essence, the proposed model provides a sophisticated, data-driven resource that empowers cultivators with the necessary intelligence to manage Arowana aquaculture with unprecedented precision and foresight, moving towards more sustainable and economically viable practices.

4.4 Strengths and Weaknesses

The evaluation and validation phases reveal both compelling strengths and identifiable weaknesses of the proposed IoT-FTS system.

4.4.1 Strengths

- High Predictive Accuracy: The foremost strength is the exceptionally high predictive accuracy of the FTS-multivariate T2 model, as consistently demonstrated by its low MAE, MAPE, MSE, RMSE, and near-perfect R2 scores. This level of precision is critical for sensitive aquaculture applications where even small deviations can have significant consequences.

- Robustness to Vagueness and Uncertainty: Fuzzy time series models inherently excel at handling imprecise, vague, and non-linear data, which are common characteristics of environmental parameters. This makes them particularly well-suited for water quality forecasting compared to crisp models that might struggle with such data characteristics.

- Multivariate Capability: The ability of the model to incorporate multiple interacting water quality parameters simultaneously (pH, temperature, turbidity, dissolved oxygen, conductivity) is a significant strength. It accounts for the complex interdependencies within the aquatic ecosystem, leading to more holistic and accurate predictions than univariate approaches.

- Scalability: The FTS-multivariate model (both T1 and T2) demonstrates considerable flexibility regarding scalability. As long as the necessary dataset and sensors are available, it can be implemented in larger aquariums or even commercial-scale aquaculture farms with only minor adjustments. The aggregation of data from multiple sensors across a larger facility is a straightforward extension.

- Adaptability: The continuous learning mechanism, where the FTS model updates its fuzzy logical relationships with new data arriving from the IoT system, ensures that the model remains adaptive to subtle changes in the cultivation environment over time, maintaining its predictive power.

- Proactive Management Enablement: This is a core strength, shifting the paradigm from reactive problem-solving to preventative action, leading to improved outcomes for fish health and cultivator economics.

4.4.2 Weaknesses

- Data Dependency: Like most data-driven models, the accuracy and robustness of the fuzzy time series model are heavily dependent on the quality, quantity, and representativeness of the historical data used for training. Insufficient, noisy, or incomplete datasets can impair its predictive capability. The initial data collection phase requires significant effort and a controlled environment.

- Specific to Time Series Data: The FTS algorithm is inherently designed for time series data. It is unsuitable for other types of datasets, such as image data, or unstructured text. This limits its direct applicability outside of temporal prediction tasks.

- Domain Specificity (Initial Training): While scalable, the model, once trained, is curated with the specific characteristics of Arowana water parameters and optimal ranges. Applying it directly to other types of fish or different aquaculture systems without retraining with a proper, relevant dataset is not recommended, as the optimal parameters and their interrelationships can vary significantly across species and environments.

- Complexity of Fuzzification and Defuzzification: While powerful, the processes of defining universes of discourse, membership functions, and defuzzification methods require expert knowledge and careful tuning. Improper configuration can negatively impact model performance.

- Computational Resources: For very large datasets and highly complex multivariate FTS models, the computational resources required for training and real-time prediction in a cloud environment, while manageable, still need to be considered.

4.5 Future Study

Building upon the success of this hybrid IoT-FTS system, several promising avenues for future research and development can be explored to further enhance its capabilities and broaden its applicability:

- Expanded Parameter Integration: Future studies could incorporate a wider array of critical water quality parameters, such as ammonia, nitrite, and nitrate levels. These nitrogenous compounds are highly toxic to fish and their inclusion would provide an even more comprehensive predictive model, allowing for earlier detection and mitigation of potential poisoning risks.

- Automated Control Mechanisms: The ultimate goal for intelligent aquaculture is a fully autonomous system. Integrating the predictive forecasting with automated control mechanisms represents a logical next step. For example, if the system predicts a drop in dissolved oxygen, it could automatically trigger aeration pumps. Similarly, a predicted rise in ammonia could activate automated water exchange systems or biofiltration. This would create a closed-loop feedback system, minimizing manual intervention.

- Hybrid Forecasting Models: Investigating more advanced fuzzy time series algorithms or developing hybrid models that combine FTS with other machine learning or deep learning techniques could further enhance forecasting accuracy and efficiency. For instance, combining FTS with Long Short-Term Memory (LSTM) networks, Autoregressive Integrated Moving Average (ARIMA), or Seasonal Autoregressive Integrated Moving Average (SARIMA) could leverage the strengths of both approaches, particularly for capturing long-term dependencies and complex non-linear patterns [27], [28], [29].

- Real-time Adaptive Learning: While the current model updates its relationships, exploring online learning algorithms that allow the FTS model to adapt its parameters or fuzzy sets in real-time with continuous data streams could improve its responsiveness to unforeseen environmental changes or long-term systemic shifts in the aquaculture setup.

- Advanced User Interface and Alerting: Developing a more sophisticated and user-friendly mobile application with customizable dashboards, advanced visualization tools (e.g., interactive charts, heatmaps of water quality), and intelligent alerting systems (e.g., push notifications, SMS alerts) would significantly enhance the system's accessibility and utility for cultivators. This could also include scenario planning tools based on predictions.

- Multi-Tank Management and Spatial Analysis: For larger aquaculture operations with multiple tanks, future work could focus on extending the system to manage multiple cultivation units simultaneously. This would involve incorporating spatial analysis to identify localized issues or propagate conditions across interconnected systems.

- Economic Impact Assessment: Conducting detailed longitudinal studies to quantify the tangible economic benefits (e.g., reduced feed waste, lower electricity consumption, increased survival rates, higher yields) resulting from the deployment of such predictive systems in commercial Arowana farms would provide robust justification for wider adoption.

- Sustainability and Environmental Impact: Further research could delve into how such intelligent systems contribute to the broader goals of sustainable aquaculture, including reduced water usage, minimized chemical inputs, and overall environmental footprint reduction.

By pursuing these future research directions, the proposed IoT-FTS framework can evolve into an even more powerful and indispensable tool for intelligent aquaculture, ensuring the long-term viability and productivity of Arowana cultivation.

CONCLUSION

Water quality stands as the paramount determinant of Arowana fish health, growth, and survival. The intricate balance of key parameters—pH, temperature, turbidity, dissolved oxygen, and conductivity—is crucial, and imbalances can lead to increased mortality rates and significant economic losses for cultivators. While previous studies have made strides in real-time monitoring using IoT technologies, a critical gap remained in their predictive capabilities, leaving cultivators in a reactive position.

This study successfully addressed this fundamental challenge by designing and rigorously evaluating a novel predictive model that seamlessly integrates the Internet of Things (IoT) with a multivariate fuzzy time series (FTS) algorithm. The IoT infrastructure enabled continuous, robust, and real-time acquisition of essential water quality data, providing an unprecedented level of insight into the aquatic environment. This data then served as the foundation for the sophisticated FTS-multivariate T2 model, which effectively captured the complex, non-linear, and often vague relationships within the water quality parameters.

The comprehensive evaluation, employing metrics such as MAE, MAPE, MSE, RMSE, and R-squared, unequivocally demonstrated the superior performance of the FTS-multivariate T2 model. It achieved an exceptionally low Mean Absolute Percentage Error (MAPE) of 0.01704%, signifying a prediction accuracy of over 99.98%. This performance significantly surpassed that of benchmark algorithms, including Decision Tree (MAPE 0.13410%), FTS-multivariate T1 (MAPE 0.88397%), and particularly Linear Regression (MAPE 20.91791%). The visual validation and robust cross-validation results further reinforced the model's consistency and generalizability across different data subsets.

In conclusion, the proposed FTS-multivariate T2 model is not only highly capable of accurately forecasting Arowana water quality but also offers a remarkably lower mean absolute percentage error compared to other predictive algorithms. This hybrid IoT-FTS framework represents a pivotal advancement in intelligent aquaculture. By empowering cultivators with proactive insights into future water conditions, it enables timely interventions, minimizes environmental stress on the fish, reduces mortality rates, optimizes resource utilization, and ultimately fosters more efficient, sustainable, and economically viable Arowana cultivation practices. This research underscores the transformative potential of integrating cutting-edge data science with environmental monitoring for the benefit of both conservation and industry.

REFERENCES

G. H. Yue, A. Chang, A. Yuzer, and A. Suwanto, “Current knowledge on the biology and aquaculture of the endangered Asian arowana,” Reviews in Fisheries Science & Aquaculture, vol. 28, no. 2, pp. 193–210, 2020, doi: 10.1080/23308249.2019.1697641.

S. R. Medipally, F. M. Yusoff, N. Sharifhuddin, and M. Shariff, “Sustainable aquaculture of Asian arowana - a review,” Journal of Environmental Biology, vol. 37, no. 4, pp. 829–838, 2016.

A. S. Panjaitan, F. Hapsari, M. Margono, and H. Al-Qoyyimah, “Variety types of natural food fish usage in the growth of super red arowana fish (Scleropages formosus),” Eduvest-Journal of Universal Studies, vol. 3, no. 4, pp. 842–849, Apr. 2023, doi: 10.59188/eduvest.v3i4.796.

J. W. Senders and N. P. Moray, Human error: cause, prediction, and reduction, CRC Press, 2020.

J. Trevathan and D. Nguyen, “Adaptive IoT technology for measuring salinity, dissolved oxygen, and pH in aquatic environments,” International Journal of Hyperconnectivity and the Internet of Things, vol. 6, no. 1, pp. 1–20, Mar. 2022, doi: 10.4018/IJHIoT.294894.

A. Rehman, T. Saba, M. Kashif, S. M. Fati, S. A. Bahaj, and H. Chaudhry, “A revisit of internet of things technologies for monitoring and control strategies in smart agriculture,” Agronomy, vol. 12, no. 1, pp. 1-21, 2022, doi: 10.3390/agronomy12010127.

A. F. Daru, F. W. Christanto, and V. Vydia, “Internet of things-based water pH level monitoring for arowana cultivation,” IOP Conference Series: Earth and Environmental Science, vol. 1177, no. 1, 2023, doi: 10.1088/1755-1315/1177/1/012004.

J. E. da Costa and A. W. R. Emanuel, “IOT design monitoring water tank study case: Instituto profissional de canossa (IPDC),” International Conference on Science and Applied Science (ICSAS) 2020, AIP Conference Proceedings, 2020, doi: 10.1063/5.0032638.

M. F. Suhaimi, N. Huda, M. Tahir, S. N. Mohamad, and S. R. Aw, “IOT based automatic aquarium monitoring system for freshwater fish,” International Journal of Synergy in Engineering and Technology, vol. 2, no. 1, pp. 125–133, 2021. [Online]. Available: https://tatiuc.edu.my/ijset/index.php/ijset/article/view/95

W. Sholihah, A. Hendriana, I. Kusumanti, and I. Novianty, “Design of IoT based water monitoring system (simonair) for arwana fish cultivation,” Eduvest-Journal of Universal Studies, vol. 2, no. 12, pp. 2872–2884, Dec. 2022, doi: 10.59188/eduvest.v2i12.708.

F. L. Toruan and M. Galina, “Internet of things- based automatic feeder and monitoring of water temperature, pH, and salinity for litopenaeus vannamei shrimp,” Jurnal ELTIKOM, vol. 7, no. 1, pp. 9–20, Jun. 2023, doi: 10.31961/eltikom.v7i1.658.

A. C. Bento, “IoT: nodeMCU 12e X arduino uno, results of an experimental and comparative survey,” International Journal of Advance Research in Computer Science and Management Studies, vol. 6, no. 1, pp. 46–56, 2018. [Online]. Available: https://scihub.se/https://pdfs.semanticscholar.org/84c4/71470cc3c8e27807df60aa5dde2888cc3b3f.pdf%0Awww.ijarcsms.com.

B. Strauch, “John senders, human error, and system safety,” Human Factors, vol. 65, no. 5, pp. 766–778, Aug. 2023, doi: 10.1177/00187208211001982.

P. C. de L. e Silva, C. A. Severiano, M. A. Alves, R. Silva, M. W. Cohen, and F. G. Guimarães, “Forecasting in non-stationary environments with fuzzy time series,” Applied Soft Computing Journal, vol. 97, 2020, doi: 10.1016/j.asoc.2020.106825.

O. Orang, R. Silva, P. C. de L. e Silva, and F. G. Guimaraes, “Solar energy forecasting with fuzzy time series using high-order fuzzy cognitive maps,” in 2020 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), Jul. 2020, pp. 1–8, doi: 10.1109/FUZZ48607.2020.9177767.

Y. Alyousifi, M. Othman, R. Sokkalingam, I. Faye, and P. C. L. Silva, “Predicting daily air pollution index based on fuzzy time series markov chain model,” Symmetry, vol. 12, no. 2, p. 293, Feb. 2020, doi: 10.3390/sym12020293.